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Machine Learning-Based Detection of Meltdowns in Autism Spectrum Disorder Individuals Using Galvanic Skin Response Signals

Edward Yoon[1] and Jongho Yoon[#]

[1]Seoul International School, Republic of Korea
[#]Advisor

ABSTRACT

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by challenges in social interaction, communication, and repetitive or restrictive behaviors. Individuals with ASD may have a range of symptoms and severity, which can include difficulty understanding and responding to social cues, sensitivity to sensory input, and a strong preference for routines. A meltdown is a common response for individuals with ASD when they are overwhelmed by sensory input, emotions, or changes in their environment. During a meltdown, the individual may lose control over their behavior, resulting in intense expressions of distress such as crying, screaming, or physical outbursts. Deep pressure therapy, such as that provided by a firm hug or weighted jacket, can be very effective in helping individuals with ASD manage meltdowns. In this research, I proposed a machine learning-based meltdown detection from galvanic skin response signals. The proposed system automatically detects meltdowns in individuals by analyzing galvanic skin response signals obtained from a wearable device. The proposed system achieved an accuracy of 86.6% which demonstrates its feasibility.

Introduction

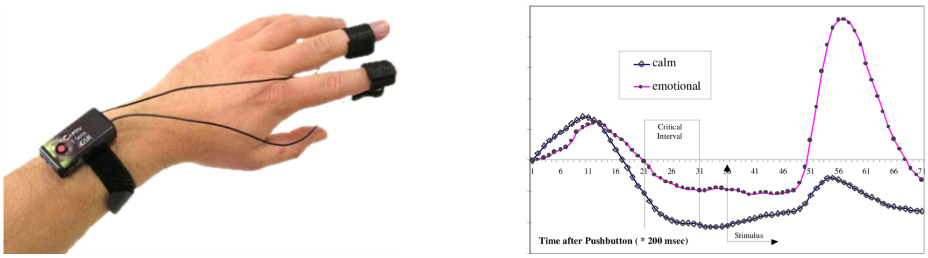
Autism Spectrum Disorder (ASD) is a developmental disorder that affects social interaction, behavior, expression of emotions, and other activities that unaffected people feel come for granted. Some common signs of ASD are delayed speech and language skills, limited use of gestures, limited eye contact, and repeating the same actions or phrases. When an individual with ASD has a dire emotion they wish to express and they have difficulty, they will throw tantrums, similar to that of toddlers in an attempt to express themselves. This is called a meltdown where these individuals react prematurely to stimuli. They often portray relentless anger leading to screaming and striking one's head. A common solution that calms children in this situation down is to hug them tight, putting pressure on their bodies. This is called deep touch pressure. Deep touch pressure stimulates the parasympathetic nervous system which is responsible for the body's rest and digestion functions. This activation helps counteract the fight or flight response associated with meltdowns which promotes a state of calmness. Meltdowns in children with ASD are intense reactions to overwhelming stimuli marked by various distress behaviors. Deep touch pressure can be a highly effective tool in mitigating these meltdowns by calming the nervous system and helping the child regain a sense of control and composure.

Inspired by this, in this research, I proposed a novel therapeutic system to assist ASD children during meltdowns. The proposed system detects meltdowns using a Galvanic Skin Response (GSR) sensor which represents changes in skin conductance related to emotional and physiological arousal. The system triggers an automatic pressure jacket to apply deep touch pressure which helps to calm the child and reduce sensory overload.

Background Knowledge

Galvanic Skin Response

A Galvanic Skin Response (GSR) utilizes the electrical currents that travel through the finger via the sweat glands in the fingers and palm (Sharma et al. 2016). This skin becomes a better conductor for electricity when something intense happens within the body or is aroused, physically or mentally. This device indicates the involuntary bodily response when exposed to stimuli which can fluctuate one's levels of arousal, whether it be positive or negative.



(a) (b)

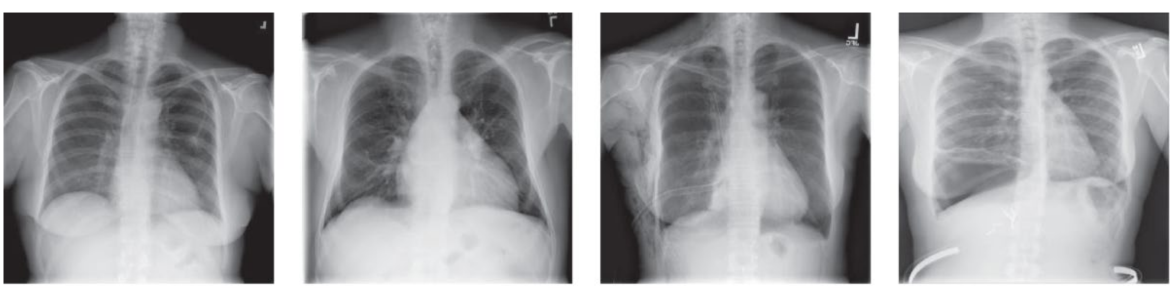
Figure 1. Galvanic Skin Response (GSR) Device and Signal Pattern
(a): GSR device, and (b): signal pattern of emotional arousal

Figure 1 (a) shows how the galvanic skin response contraption works and how it is a very convenient simple device that reads signals from the fingers. Figure 1 (b) shows the data received from the GSR where emotion can be analyzed through signals from the contraption.

Classification System

The classification system that will be used will consist of input data, a process that runs probability, and a system that assigns the data into a fixed set of categories.

In general, a machine learns using the Convolutional Neural Network, or more commonly known as the CNN, which is what this project will be using for data classification and machine improvement.



(a) "No Finding" **(b)** "Cardiomegaly" **(c)** "Pneumothorax" **(d)** "Pneumothorax"

Figure 2. Example of image classification (chest x-ray classification) (Baltruschat et al 2019).

For example, as shown in Figure 2, chest X Rays can show if a person has been infected by COVID or not through this technology that classifies data. As shown in the images below, using this classification method, the machines can make out if there are any abnormalities that result in, in this situation, COVID.

In this research, I proposed a GSR signal classification system to detect autistic meltdown status which distinguishes between arousal and calm emotional states. A detailed explanation of the proposed system is provided in Chapter 3.

Proposed Method

Figure 3 illustrates the overall architecture of the proposed meltdown detection system. The system takes galvanic skin response signal as input and predicts the probability of having a meltdown. The system is developed with convolutional neural networks and fully connected neural networks. Galvanic skin response signal is fed into the 1-D convolutional neural network and converted into feature maps that mathematically represents the features of inputted galvanic skin response. These feature maps are processed into meltdown classification network to predict the probability of having a meltdown. I consider this meltdown detection as a binary classification task.

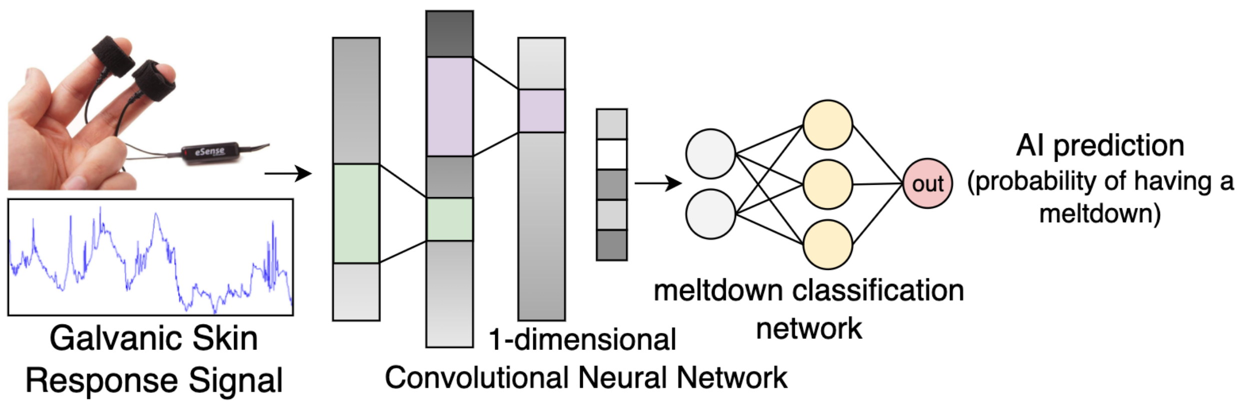


Figure 3. Architecture of the proposed meltdown detection system

To train the proposed meltdown detection system, I utilized the binary cross entropy loss function as shown in Equation 1. The binary cross entropy loss function is often used to train classification models that classifies inputs into one of two possible classes (Lu and Weng 2006).

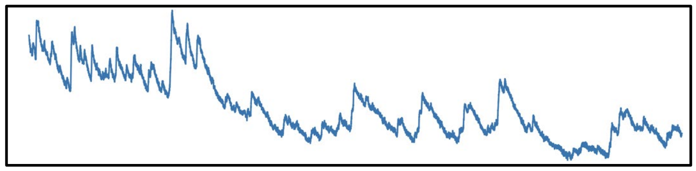
Equation 1: Binary cross entropy loss function

$$Loss_i = -[gt_i log_e(\widehat{out}_i) + (1 - gt_i) log_e(1 - \widehat{out}_i)]$$

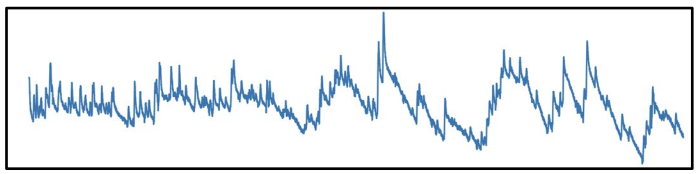
Here, ***out*** and ***gt*** denote the predicted probability of having a meltdown and its ground truth. For the convolutional neural network, I employed four different types of architectures that have comparable performance in many classification problems. To implement a meltdown classification network, I developed two-layered fully connected neural networks. I trained a proposed system for 100 epochs with a batch size of 512. The initial learning rate is set to 0.0001 and applied to a stochastic gradient descent algorithm with momentum value of 0.9.

Experimental Results

To train and evaluate the proposed system, I first utilized the PhyAAt dataset (Bajaj et al.2021) where 25 people(21 males, 4 female) were used and 270 samples were obtained per person, resulting in 6750 samples. The two graphs below track the waves from the galvanic skin response.



(a)



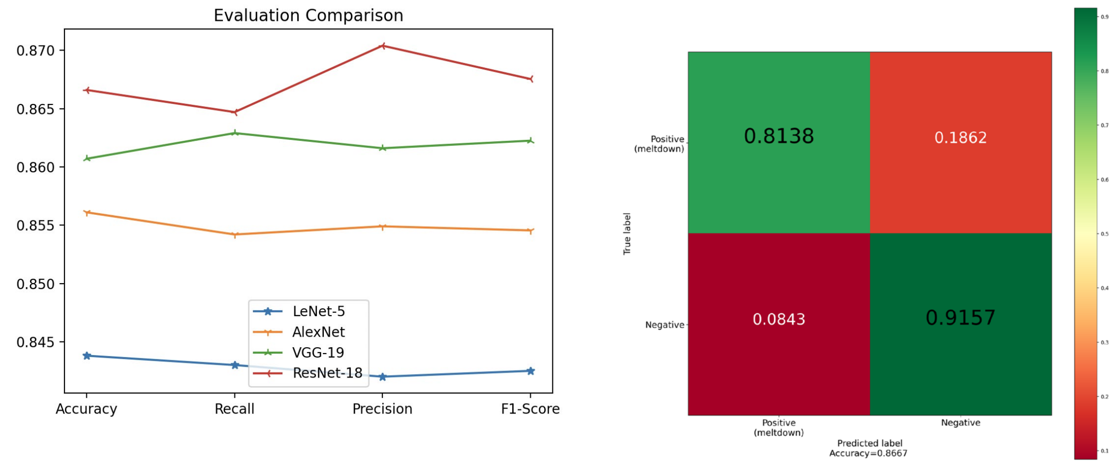
(b)

Figure 4. Sample example of the dataset used in this paper
(a): normal condition and (b) meltdown condition

I utilized four convolutional neural network architectures including LeNet-5 (LeCun et al. 1998), AlexNet (Krizhevsky et al. 2012), VGG-19 (Simonyan et al. 2014), and ResNet-18 (He et al. 2016). Among the four architectures, ResNet-18 achived the most accurate result with an accuracy of 0.8666. They are also further supported by the diagrams below of the (a): performance comparison graph and (b): confusion matrix of ResNet-18 in Figure 5.

Table 1. Performance comparison for four convolutional neural network architectures

Architecture	Accuracy	Recall	Precision	F1-Score
LeNet-5	0.8438	0.8430	0.8420	0.8425
AlexNet	0.8561	0.8542	0.8549	0.8545
VGG-19	0.8607	0.8629	0.8616	0.8622
ResNet-18	0.8666	0.8647	0.8704	0.8675



(a) (b)

Figure 5. (a): performance comparison graph and (b): confusion matrix of ResNet-18

Figure 5 (b) illustrates the confusion matrix evaluation result of ResNet-18. The top left and bottom right cells represent the true positive (meltdown) and true negative ratio. Both evaluation results are accurate, achieving correct ratios of 81.3% and 91%, respectively, which clearly demonstrates the feasibility of the proposed approach.

In addition, I conducted a user study to examine how the proposed meltdown detection system performs in real-world scenarios. I collected data from 8 subjects, each of whom experienced 10 calm states and mimicked 10 meltdown situations, such as watching very unpleasant videos or experiencing overwhelming stimuli like being yelled at.

I evaluated two models: the proposed meltdown detection system and a fine-tuned model tailored for each individual. Table 2 and Figure 6 summarize the user study results. Surprisingly, the proposed system achieved 68.1% and 71.7% accuracy in the user study, which are comparable results even for real-world scenarios. These results can be significantly improved by simply applying fine-tuning with each individual's collected data. The accuracy of ResNet-18 improved by 13%, and VGG improved by 13.8%. This experiment clearly shows that applying fine-tuning methods can greatly enhance accuracy when applied to real-world scenarios.

Table 2. Fine-tuning experiment results

Architecture	Accuracy	Accuracy (fine-tuning)
VGG-19	0.6812	0.8201
ResNet-18	0.7172	0.8474

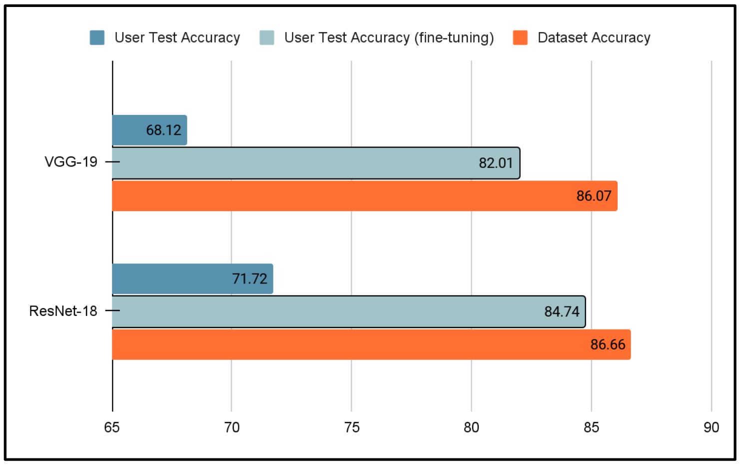


Figure 6. Fine-tuning experiment results graph

Conclusion

In this research, I proposed a machine learning-based meltdown detection system using galvanic skin response signals. The system was developed using four different convolutional neural networks, each demonstrating comparable classification performance. The system achieved an accuracy of 86.6% on the phyAAt dataset, proving its feasibility for real-world applications. Additionally, I demonstrated that fine-tuning for individuals can greatly enhance meltdown detection accuracy. In the future, I plan to implement the developed system in a wearable device for individuals with ASD. I hope that through this research, individuals experiencing autistic meltdowns will be better able to manage their situations.

Acknowledgments

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